Journal of Transport Geography 129 (2025) 104397

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Evolving transport mode changes: A longitudinal analysis of built-environment exposure in Montréal, Canada

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ARTICLE INFO

Keywords:
Longitudinal travel behavior
Mode share
Built environment exposure
Panel modeling
Home relocation

ABSTRACT

Understanding the impacts of exposure to local and regional accessibility on travel behavior is essential to develop long-term effective land-use and transport policies. Previous research concentrating on accessibility impacts were mostly of cross-sectional nature and were conducted using pre-pandemic data. This study examines the longitudinal relationships between exposure to different levels of local and regional accessibility and mode use, focusing on how home relocation affects the frequency of use of the three major transport modes: active transport, driving, and public transit. The study uses five waves (2019–2024) of the Montréal Mobility Survey, to analyze 4550 panel respondents, split into worker ($N = 3067$) and non-worker ($N = 1483$) subsamples. Using a set of multilevel linear regressions and a cumulative exposure measure, this work analyzes the gradual impacts of home relocation and changes in exposure levels to regional and local accessibility on weekly mode use frequency over time while controlling for car ownership and household structure. The study provides robust longitudinal evidence on how residential relocation, built-environment exposure, and concurrent life decisions collectively reshape urban travel behavior in the post-pandemic era across different transport modes. The multilevel modeling approach reveals three key insights: (1) regional and local accessibility changes (through relocation) exert gradual and mode-specific effects, with active transport showing the strongest response; (2) while workers and non-workers show varying baseline travel patterns, both groups respond similarly to local and regional accessibility improvements and changes in car ownership; and (3) car ownership decisions can significantly moderate the effects of home relocation. These findings advance the methodological integration of longitudinal exposure measures to levels of accessibility in mobility research.

1. Introduction

Urban mobility systems face unprecedented challenges, from climate commitments to post-pandemic behavioral shifts. Understanding how and why people travel, and how these patterns change over time, is essential for long-term land use and transport policies. Given the complexity of studying the temporal dynamics of travel behavior, most studies focus on cross-sectional framings, failing to capture the dynamic interplay between life transitions, changing built environments, and transport decisions. This gap is particularly critical today in the rapidly changing context of the post-pandemic world.

Longitudinal approaches that disentangle gradual adaptations are essential to designing policies that align with current behavioral trajectories. Previous studies have focused deeply on evolving travel behavior through the lens of changing lifestyles and mobility biographies (Müggenburg et al., 2015), analyzing how travel patterns vary for individuals over time. Key triggers have been found to correlate with changes in these dynamics, such as home relocation, mobility decisions such as buying a car, and changes in household structure (Adhikari et al., 2020; Lee et al., 2017; Wasfi et al., 2016). However, existing longitudinal studies were either done in the pre-pandemic context (De Vos et al., 2018; Wasfi et al., 2016); performed simple before-after comparisons ignoring gradual temporal adaptation (Adhikari et al., 2020; Schimohr et al., 2025); or focused narrowly only on one mode of transport (Faber et al., 2025; Xu et al., 2024). Addressing these three gaps is critical because pre-pandemic findings may not reflect current mobility trends, simple before-after comparisons overlook gradual adaptations essential for policy timing, and a single-mode focus ignores substitution effects which are relevant for integrated transport planning.

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https://doi.org/10.1016/j.jtrangeo.2025.104397
Received 21 April 2025; Received in revised form 21 August 2025; Accepted 22 August 2025
Available online 27 August 2025

This study aims to advance longitudinal mobility research by analyzing how key behavioral triggers – particularly residential relocation, car ownership changes, and changes in household structure - reshape mode use patterns in the post-pandemic context. Using a five-wave longitudinal survey between 2019 and 2024 in Montréal, Canada, this work analyzes the dynamics of mode-use patterns across all major transport modes: active transport, driving, and public transit. Through a set of multilevel linear regressions, this study analyzes the factors affecting the frequency of use for the three stated modes of transport while tracking gradual adaptations to local and regional accessibility changes through an exposure measure. By allowing the decay rate of past exposures to vary by transport mode, the models capture distinct temporal patterns in behavioral adaptation across active, transit, and car travel. This approach explicitly accommodates potential differences in the temporal evolution between modes. Moreover, these models disentangle pandemic-related disruptions from lasting behavioral shifts and compare how these dynamics differ between workers ($N = 3067$) and non-workers ($N = 1483$).

Findings in this work provide actionable insights for planners and policymakers navigating post-pandemic mobility challenges. By quantifying how relocations between built environments interact with life-stage decisions across population groups, the results suggest priorities to local and regional accessibility improvements through land-use and transport measures.

2. Literature review

The study of travel behavior dynamics refers to the analysis of how and why individuals' mobility patterns evolve over time. Multiple dimensions have been shown to affect these dynamics, such as lifecycle events (Lee et al., 2017; Zhang et al., 2024), exogeneous trends and events (Khalil et al., 2024; Victoriano-Habit and El-Geneidy, 2024), and changes in the built environment and transport systems (Heinen et al., 2017; Spears et al., 2017; Sun and Du, 2023). These dynamics have been conceptualized to occur at different timeframes, from daily and weekly scheduling to life-long aging processes (Clarke et al., 1982). Changes in the medium-long term, which this study concerns with, are generally linked to large "life shocks" (Goodwin, 1997). Many studies have inquired into the trajectories of travel-behavior changes over time using *mobility biographies* (Scheiner, 2007, 2018). Through a systematic review, Müggenburg et al. (2015) found that the main key events discussed under this framework are: (i) private and professional life events such as changing jobs or birth of a child, (ii) adaptation of long-term mobility decisions such as purchasing a car, (iii) exogeneous interventions such as new infrastructure, and (iv) long-term processes such as aging and generational effects.

In order to understand temporal trends of travel behavior and their direction, repeated observations of the same individuals through time are required (Clarke et al., 1982; van de Coevering et al., 2015). As mentioned by Goodwin (1997) regarding urban-transport temporal trends, "*even apparently settled aggregate patterns are based on a very high degree of volatility, movement and turnover at the individual level*". This means that observed aggregate patterns may have hidden 'sub-trends' that are not observable by aggregate, cross-sectional, or repeated cross-sectional data. This is particularly relevant in the post-COVID context, where emerging mobility trends (Wang et al., 2022; Zhao and Gao, 2022) and evolving relationships with the built environment (Negm and El-Geneidy, 2024; Victoriano-Habit and El-Geneidy, 2024) highlight the need for disaggregated longitudinal data to unravel behavioral shifts.

Studies using panel data to analyze travel behavior dynamics have shown that shifts are deeply intertwined with life stage and household structure changes. Lee et al. (2017), using ten waves of panel mobility data, studied the triggers of behavioral change within a household. They found that the evolution of a household's composition, particularly in terms of the number of children, is the main trigger of change. Similarly, Zhang et al. (2024) highlight how life events reshape travel attitudes and mode choices, with gender moderating these transitions. Khalil et al. (2024) showed the impact of demographic events to predict broad urban mobility impacts. These studies highlight that lifestyle transitions disrupt habitual travel patterns, particularly those related to mode choice and frequency of use (Adhikari et al., 2020). Moreover, these changing patterns often occur in highly mode-specific ways (Faber et al., 2025; Xu et al., 2024).

The contribution of exogenous components has shown to be significant in shaping travel behavior through time. The concept of accessibility, central in transport discussions for more than four decades, has been effective in reflecting the impacts of changing land-use and transport systems (El-Geneidy and Levinson, 2022; Geurs and van Wee, 2004; Hansen, 1959). Reflecting exogeneous conditions through accessibility has been thoroughly incorporated into longitudinal travel behavior studies (Busch-Geertsema and Lanzendorf, 2015). Within this context, residential relocations are particularly interesting, as they have the potential to combine relevant changes in lifestyle and life stage with changes in the residential accessibility levels. Studies have shown that these relocations gradually change both travel behavior and attitudes, especially when moving between different built environments (De Vos et al., 2018). Moreover, the effects may vary between different sociodemographic groups (Cheng et al., 2019), and impact transport modes in different ways over time (Schimohr et al., 2025). To properly capture these complex temporal dynamics, exposure measures have proven valuable in revealing the gradual, long-term behavioral adaptations that occur after relocation between different built environments (Wasfi et al., 2016).

A relevant distinction in the use of accessibility within travel behavior studies is that between *local accessibility* and *regional accessibility* (Handy, 1993, 2020; Manaugh and El-Geneidy, 2012). Local accessibility is more related to density and proximity, and thus is more related to active modes such as walking and cycling (Manaugh and El-Geneidy, 2011). As regional accessibility is related to speed, it is clear that it has a closer relationship to motorized modes: the private car and public transport (Lussier-Tomaszewski and Boisjoly, 2021; Silva and Altieri, 2022). This distinction has shown to be useful when evaluating travel behavior dynamics and the effect of residential relocations (Lee et al., 2017; Wasfi et al., 2016).

Although multiple longitudinal studies have contributed to understanding evolving mobility patterns, particularly those related to mode use and home relocation, significant gaps remain. Existing studies either (1) were done in the pre-COVID context (De Vos et al., 2018; Wasfi et al., 2016), (2) perform simple before-after comparisons ignoring gradual temporal adaptation (Adhikari et al., 2020; Schimohr et al., 2025), or (3) focus narrowly only on one mode of transport (Faber et al., 2025; Xu et al., 2024). These research gaps are critical to address both for research and policymaking. First, pre-pandemic studies risk offering outdated insights, as COVID-19 has reshaped fundamental relationships, including that between travel behavior and the built environment (Negm and El-Geneidy, 2024; Victoriano-Habit and El-Geneidy, 2024). Second, reliance on simple before-and-after comparisons overlooks potential gradual adaptations such as delayed mode shifts (Chang et al., 2010; Chatterjee and Ma, 2007, 2009). Third, a narrow focus on a single transport mode ignores the potential substitution dynamics between different transport modes (Sun and Du, 2023; Sun et al., 2020). This study addresses these three limitations by analyzing five waves of panel data, spanning the pandemic period, and employing exposure measures to track gradual behavioral change across active, driving, and transit modes.

3. Data

3.1. Montreal mobility survey

The primary dataset of this study is composed of the panel responses from the first five waves of the Montréal Mobility Survey (MMS) (Negm et al., 2023; Victoriano-Habit et al., 2024). These five waves were collected in 2019, 2021, 2022, 2023, and 2024 through an online bilingual survey administered in the Greater Montréal Area to participants aged 18 years or older. To ensure sample representativeness, various recruitment techniques recommended by Dillman et al. (2014) were employed in all waves. These included the distribution of flyers at various residences and transport hubs, as well as targeted online recruitment through paid and un-paid advertisements on various social media platforms. Incentives were included in the survey such as the possibility of winning a prize based on a draw. A public opinion survey company was hired during all waves to help in recruiting part of the sample. All survey respondents who provided an email address received an invitation to participate in all subsequent waves. Through this process, the survey sample was composed of both respondents who participated in only one wave (cross-sectional) and those who participated in two or more waves (panel), which are the interest of this study.

The same data-cleaning process was applied to all waves of the survey to ensure consistency in the exclusion criteria of unreliable responses. These exclusion criteria included several sequential filters. Repeated responses entered by the same e-mail or IP address were removed. Invalid age and height changes between waves were also filtered. In terms of survey-response time, the fastest 5 % were excluded from the sample depending on the number of questions answered in each wave. Different groups of respondents, depending on their answers, got different sets of questions. Each of these groups were cleaned according to their own respective top 5 % speed. The 5 % threshold was determined by plotting response times in ascending order and identifying a natural break point in the distribution, which consistently appeared around the fastest 5 % of responses. Spatial filters were also applied. Those who placed a pin representing their home, school and/or work location outside the Montréal metropolitan region were excluded. Participants who reported no weekly trips were removed from the sample. This thorough validation process resulted in a final sample size of 4550 respondents who participated in at least two of the five survey waves. This work separates the panel sample into two sub-samples (Fig. 1). The sub-sample of workers ($N = 3067$) is composed only of those employed full- or part-time in all waves of the survey with a valid work trip. Similarly, the sub-sample of non-workers ($N = 1483$) are respondents with no employment in every wave they responded to.

All waves of the survey included the same questions pertaining to weekly mode-use frequency. Trips by active modes of transport, driving, and public transit were recorded by respondents for four distinct travel purposes: work, school, grocery shopping, and healthcare. Only home-based trips were recorded, and return trips are not counted. Each travel mode and purpose combination were measured consistently. Respondents reported the number of trips made in the last week on a discrete scale from 0 to 10 for each trip purpose by each mode. The uniform measurement structure across modes helps ensure comparability and minimizes the risk of measurement sensitivity. To reduce the influence of extreme values in the dependent variable, respondents reporting zero total trips or more than 40 total trips per week were excluded. Additionally, a more conservative filter was tested, capping total trips per mode at 10 across all purposes. Results remained substantively unchanged, indicating that findings are robust to outlier treatment. For workers, each survey wave collected information pertaining to weekly commuting and telecommuting behavior. Commuting time by driving and public transit was extracted from Google Maps API for the time and day reported by the participant. Respondents' socio-demographic characteristics were collected in all waves. Most importantly, since every question was answered by participants at least in two points in time, changes in all variables can be measured through time. Because the analysis uses panel data which tracks the same individuals over time, residential self-selection becomes less of a concern than in cross-sectional studies (van de Coevering et al., 2015). Individuals carry their attitudes toward travel in their residential relocations. This allows for behavioral changes to be more accurately assumed as a response to the changes in surrounding built environment rather than a product of attitudes toward residential selection.

Participants' home locations were reported through one of two methods, by the respondent's choice: through placing a pin on a map or by providing the postcode of their home location. Since Canadian postal code is defined at the block-level, centroids are generally precise to within 100 m of the true home location. Rates of residential moving were assessed first only for respondents who provided their home location through postal codes, assuming that a move occurs only when there is a change in postal code. Given the high level of precision, this postal-code-based approach served as the benchmark for determining an equivalent distance threshold for map-pin respondents. Through a comparative analysis, a 1600-m threshold for pin placements produced moving rates equivalent to those observed in the postal code group, ensuring consistent mobility detection across both reporting methods. Thus, for respondents using a pin on a map, a residential move was deemed to happen if the distance between two reported locations collected in two surveys was at a distance of 1600 m or more.

An attrition analysis was conducted to assess the representativeness of the panel sample across waves. Models predicting panel retention were estimated for each subsequent wave. No consistent patterns emerged from this analysis, indicating no significant issues with attrition. For this study, all responses included in the analysis were complete, with the exception of income. For this variable, missing values were

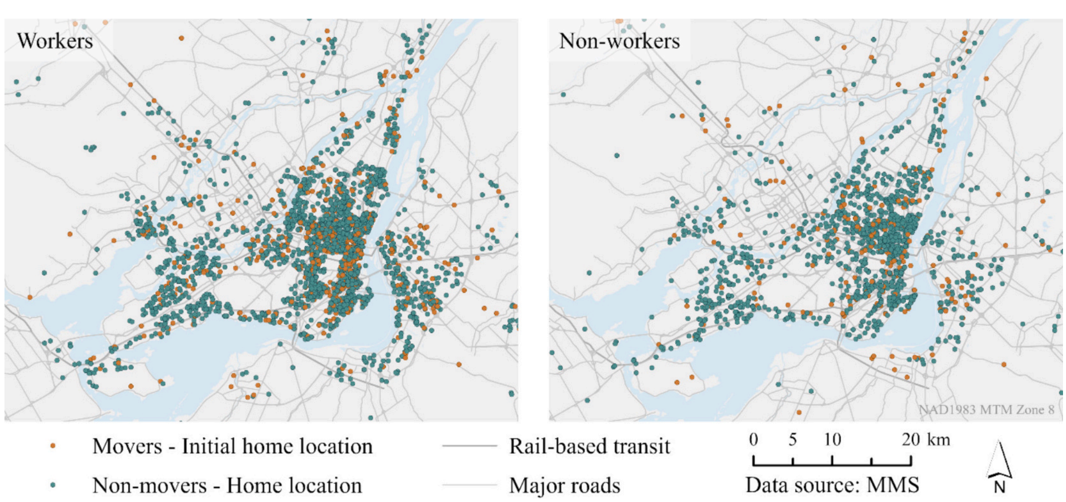

Fig. 1. MMS panel subsamples of workers and non-workers.

imputed using Multivariate Imputation by Chained Equations (MICE) using the *mice* package in R (van Buuren and Groothuis-Oudshoorn, 2011). Imputation was based on respondents' age, employment status, homeownership, household size, and education level. The Montréal Mobility Survey dataset has been widely used in travel behavior research (Carvalho and El-Geneidy, 2024; Negm and El-Geneidy, 2025; Victoriano-Habit and El-Geneidy, 2023, 2024), supporting its relevance and applicability for longitudinal transport studies. More details on its collection, data cleaning, and description can be found in Negm et al. (2023) and Victoriano-Habit et al. (2024).

3.2. Accessibility exposure measures

To evaluate the impacts of exposure to different built environments, access to opportunity measures are used in this work as they are the most comprehensive land use and transport measures (Wachs and Kumagai, 1973). Accessibility is a mode specific tool (El-Geneidy and Levinson, 2022) that reflects the built-environment characteristics in a unique way (Geurs and van Wee, 2004). To assess the impacts of access to opportunities at different urban scales and by different transport modes, measures are typically subdivided into *local accessibility* and *regional accessibility* (Handy, 2020). Accordingly, this work uses measures that separately evaluate exposure to different local and regional accessibility environments.

In this work, regional accessibility by public transport is measured using a cumulative-opportunities indicator, which considers access to all jobs within the region within a 45-min threshold. This indicator is commonly used in accessibility measurement, primarily because of its straightforward interpretation (El-Geneidy and Levinson, 2022). The 45-min threshold was chosen as it aligns closely with the median transit travel time in the Montréal region, as suggested by Kapatsila et al. (2023). To calculate this measure, transit travel times were computed between the centroids of census tracts (CTs) for a typical weekday during the morning peak period from 8:00 to 9:00 AM, using the "r5r" package (Pereira et al., 2021). While this work uses morning peak accessibility, previous works have shown that this measure strongly correlates with accessibility throughout the day and performs similarly in mode choice models (Boisjoly and El-Geneidy, 2016). CTs were selected as the unit of analysis since job data from the 2016 census commute flows (Statistics Canada, 2018) was available at this level. The calculation of transit travel times required the use of Global Transit Feed Specification (GTFS) data and the OpenStreetMap (OSM) street network, which were collected for each wave's respective year. This approach ensures that changes in public transport services are reflected in the variations of accessibility over time throughout the five survey waves.

The WalkScore index is used to measure local accessibility levels, which was retrieved from *walkscore.com* for each respondent's home location at each survey year. WalkScore is a popular measure of local accessibility which has been repeatedly tested in the land-use and transport literature (Hall and Ram, 2018), and has shown reliability in predicting active travel patterns (Manaugh and El-Geneidy, 2011). This index is produced through a gravity-based assessment of amenities within a 30-min walk of a location (Walk Score, 2022). The index considers several types of amenities, including grocery stores, schools, parks, and restaurants. The value of WalkScore ranges from 0 to 100, where higher values indicate higher levels of local accessibility. Local-accessibility data in this work accounts for changes in residential local accessibility both in the case of respondents moving house or due to changes in time. This data was collected yearly with each survey wave to represent the most recent local accessibility measure.

To measure exposure to different built environments, this work builds on the Proportional Cumulative Exposure measure (PCET) developed by Wasfi et al. (2016). In this work, the proportional cumulative exposure measure $PCETrk_{it}$ for accessibility range i at time point t is defined as:

$$PCETrk_{it} = \frac{\sum_{s=1}^{t}(rk_{is} \bullet \Delta T_{is})}{(T_{it})^{\alpha}} \quad (1)$$

Where:

- rk_{is}: binary variable indicating if the person lives within accessibility range i at time point s.
- ΔT_{is}: time elapsed between time point s and the previous survey wave in which the respondent participated.
- $T_{it} = \sum_{s=1}^{t}(\Delta T_{is})$: cumulative time of the participant in the study until time point t.
- α*:* time decay exponent controlling how sharply the impact of past exposures decays over time.

A time decay exponent of $\alpha = 1$ results in the original measure proposed by Wasfi et al. (2016), simply representing the proportion between (1) the cumulative number of years that a respondent has lived in a certain built environment category, and (2) the number of years that the respondent has participated in the study. In this work, the addition of a decay exponent allows for the measurement of how steeply the effect of past exposure decays. Higher values of α correspond to a faster response to current exposure, with a lesser impact of past exposures. Conversely, lower values of α correspond to a greater importance of past exposure and a slower adaptation to new environments. The estimation of α is done separately for each transport mode to assess the potentially different decay rates of different transport modes.

PCET enables more accurate comparisons of how sustained exposure to specific environments influences mobility behaviors, overcoming limitations of simple binary or snapshot exposure measures that fail to capture duration effects (Wasfi et al., 2016). To evaluate exposure to different accessibility levels, four groups (rk_{it}) are defined for each accessibility measure: low, mid-low, mid-high, and high. For exposure to local accessibility, PCET is calculated for the four groups defined by Walk Score (2022): car dependent (0 to 49), somewhat walkable (50–69), very walkable (70–89), and walker's paradise (90–100). In the case of regional accessibility by public transit, PCET is calculated for the four quartiles of accessibility by public transit for the entire Greater Montreal Area by census tract. The use of these ranges is consistent with previous works both in the case of WalkScore (Victoriano-Habit and El-Geneidy, 2023; Wasfi et al., 2016) and accessibility by transit (Boisjoly et al., 2020; Chia and Lee, 2020). Alternative specifications for these ranges were tried, including different thresholds and a greater number of ranges. These alternative specifications offered similar results. Thus, the ranges described above were chosen in this study for their consistency with the literature and parsimony.

4. Methods

4.1. Multilevel linear regressions

To achieve the goal of modeling evolving mode-use patterns, a set of multilevel longitudinal linear regressions is used. Each model estimates an individual's weekly frequency of use for a specific transport mode. Moreover, the panel sample is subdivided into workers' and non-workers' subsamples, as they exhibit markedly different patterns and levels of complexity of travel (Chowdhury and Scott, 2020; Dharmowijoyo et al., 2018). Furthermore, analyzing these two groups separately has become particularly relevant in the current context of increased popularity of telecommuting. These changes in working patterns have shown to beget large changes in travel patterns (Javadinasr et al., 2022; Victoriano-Habit and El-Geneidy, 2023). Three models are estimated for each of these two subsamples, one for each of the transport modes analyzed: active modes, driving, and public transport.

The data is coded in its long format, meaning that a respondent is represented in the database in as many rows as valid responses they provided. Therefore, the models estimate the frequency of weekly mode use for a specific survey wave. The multilevel structure of the model considers the fact that multiple observations correspond to the same respondent, given that each respondent participated in at least two survey waves. Thus, in the multilevel structure, person is the higher level and person-wave is the lower level. Through dummy variables representing wave fixed effects, temporal shocks affecting all respondents are measured. This includes variations between survey waves, for example, due to COVID-19 and other broader trends. Alternative model specifications were tested including interactions between wave fixed effects and key predictors such as exposure measures and car ownership. These interactions assessed whether the pandemic significantly affected the effect of such predictors. None of the interaction terms ultimately showed statistically significant effects, for which they were not included in the final models.

The explanatory variables included in each model relate to personal characteristics and exposure measures to different accessibility levels. The estimation of separate worker/non-worker models allows for the evaluation of the impact of commuting and telecommuting patterns on workers' evolving travel dynamics. For all models, personal characteristics include yearly household income, gender, number of people in the household, and number of cars in the household. Exposure to different accessibility environments is included through an indicator that builds on the Proportional Cumulative Exposure measure (PCET) developed by Wasfi et al. (2016). As explained in the previous section, a time-decay exponent (α) is added to the original PCET measure. This exponent controls how rapidly the influence of past exposures diminishes over time. Higher values of α indicate faster rate of adaptation. Each transport mode (active, transit, driving) was allowed to have a unique exponent value for each worker and non-worker subsamples. This reflects potential differences in adaptation speeds across modes and subgroups. All models were estimated multiple times for different values of α, in values ranging from 0 to 5 in increments of 0.01. The value that maximizes the model's marginal R^2 was chosen as the final decay exponent for each mode. In all cases, a value of α that produces a global maximum was found. Thus, the best decay is chosen for each mode and subsample, representing different adaptation rates to different environments.

All models take the form of standard multilevel linear equations, where the dependent variable (weekly mode-use frequency) is modeled as a linear function of fixed-effect predictors (personal characteristics, exposure measures, etc.) and random intercepts by individual. The random effects structure accounts for unobserved heterogeneity between individuals. In other words, taking into account that travel behaviors are strongly person-specific. This specification aligns with various longitudinal travel behavior research in the existing literature (El-Assi et al., 2017; Faghih-Imani et al., 2014; Victoriano-Habit and El-Geneidy, 2023, 2024). This method simultaneously: (1) captures within-person evolution of mode use over time, (2) controls for stable individual differences that could bias estimates, and (3) the coefficients of this type of model are easily interpretable as the marginal effect of independent variables on the explained variable. All multilevel linear regressions were estimated through the 'lme4' R package (Bates et al., 2015), which fits models by restricted maximum likelihood (REML).

For the active-transport model, PCET to local accessibility levels (WalkScore) is included. On the other hand, for the driving and public transit models, PCET to regional accessibility (cumulative opportunities by public transit in 45 min) is included. For the worker subsample, commuting characteristics are included in the model through two variables. First, commuting time by car is used as a measure of the person's proximity to their workplace. The second variable is the number of days per week that the respondent reported to work from home to capture the effects of telecommuting.

4.2. Scenario-based analysis

To clearly illustrate the time-evolving effects of exposure to different built environments when moving home, a scenario-based analysis is performed. In this analysis, the models are used to predict weekly mode use for several proposed profiles of people, evaluating their mode-use trajectories over time. The main goal of this analysis is to demonstrate how the estimated models are capable of representing travel behavior trajectories using the PCET framework described in Section 3. This is achieved by simulating a set of proposed profiles that isolate the effects of changing accessibility levels by home relocation while holding other sociodemographic and temporal factors fixed at proposed values. In this sense, the goal of this scenario analysis is not to predict absolute mode-share values for specific populations, but rather to elucidate the relationships between accessibility changes, mode-specific adaptation rates (α), and resulting behavioral trajectories.

First, a set of four profiles are defined, all of which are analyzed as workers and non-workers. For these profiles, all characteristics are set fixed at one level, only varying exposure to accessibility, simulating a residential relocation:

- **Profile 1 (P1):** Moving *low* to *high* accessibility
- **Profile 2 (P2):** Moving *low* to *mid-high* accessibility
- **Profile 3 (P3):** Moving *mid-high* to *low* accessibility
- **Profile 4 (P4):** Moving *high* to *low* accessibility

All other variables are fixed in the models, as follows. First, the wave fixed effects are set for wave 5 (2024) as this is the latest wave in the study. Given that the largest changes between waves that are encompassed within the fixed effects are related to the pandemic and its recovery, this is similar to assuming no further post-COVID recovery in mode shares. The household structure is set at the median size, with no children. All profiles are set to be women, with average income, average age at baseline, and no cars. Additionally, when performing this analysis with the workers' models, commuting time by car is set at the range of 30 to 60 min, and no days working from home. Most importantly, none of the particular values fixed for the profiles carry major relevance. This is because the main goal is to isolate the effect of the residential move, and the conclusions extracted from this analysis would be analogous even when changing any of these fixed variables.

To illustrate the joint effect of home relocation with other changes in lifestyle and mobility decisions, another set of four profiles is proposed. The following profiles are identical to the previous four, with the addition of either (1) getting a car if the move happens toward a lower accessibility level or (2) selling (get rid of) a car if the move is toward higher accessibility:

- **Profile 5 (P5):** Moving *low* to *high* accessibility + selling car
- **Profile 6 (P6):** Moving *low* to *mid-high* accessibility + selling car
- **Profile 7 (P7):** Moving *mid-high* to *low* accessibility + getting car
- **Profile 8 (P8):** Moving *high* to *low* accessibility + getting car

All other characteristics are set fixed in these profiles at the same values as profiles P1 through P4, with the exception of car ownership. For profiles selling a car (P5 and P6), the number of cars in the household is initially set at one (pre-move). For profiles getting a car (P7 and P8), the initial number of cars is zero.

5. Results

5.1. Descriptive statistics

Both panel subsamples used in this work are described through summary statistics in Table 1 for each of the five survey waves. First, it is important to note that sample sizes between waves vary due to different wave participation by respondents. Although all participants in the analyzed samples are repeated observations, they may not have participated in all waves. The workers' sample is composed of 7219 observations from 3067 respondents, whereas the non-workers' sample is

Table 1
Descriptive statistics by subsample and survey wave.

Variable	Workers $N = 3067$					Non-workers $N = 1483$				
	Mean (std dev.)					Mean (std dev.)				
	2019	2021	2022	2023	2024	2019	2021	2022	2023	2024
Sample size										
Movers	0	186	160	204	178	0	50	61	61	66
Non movers	941	1184	1356	1680	1330	309	644	772	804	676
Total sample	941	1370	1516	1884	1508	309	694	833	865	742
Personal characteristics										
Age in 2019	40.70 (12.64)	41.10 (12.45)	41.92 (12.37)	40.11 (12.83)	39.27 (12.72)	60.20 (12.88)	62.35 (11.15)	62.28 (10.73)	61.64 (11.28)	60.96 (11.06)
Yearly income ($10 k CAD)	9.42 (5.04)	10.55 (5.03)	10.67 (5.12)	11.20 (5.95)	12.28 (6.06)	6.56 (3.94)	7.43 (4.41)	7.34 (4.41)	7.63 (4.75)	8.51 (5.44)
Household size	2.60 (1.25)	2.53 (1.24)	2.45 (1.23)	2.45 (1.25)	2.54 (1.26)	1.99 (0.97)	1.92 (0.88)	1.82 (0.80)	1.85 (0.85)	1.87 (0.89)
Children in the household	0.43 (0.83)	0.43 (1.04)	0.37 (0.84)	0.35 (0.74)	0.37 (0.74)	0.13 (0.54)	0.08 (0.38)	0.06 (0.34)	0.08 (0.43)	0.09 (0.45)
Cars in the household	1.09 (0.90)	1.09 (0.89)	1.08 (0.88)	1.07 (0.86)	1.04 (0.85)	1.00 (0.73)	1.05 (0.74)	0.99 (0.71)	0.97 (0.68)	0.98 (0.74)
Accessibility metrics										
WalkScore										
Low (0 to 50)	13 %	12 %	12 %	13 %	13 %	16 %	18 %	17 %	13 %	14 %
Medium-low (50 to 70)	18 %	17 %	17 %	16 %	16 %	19 %	19 %	18 %	19 %	18 %
Medium-high (70 to 90)	23 %	26 %	28 %	30 %	30 %	32 %	29 %	33 %	35 %	34 %
High (90 to 100)	46 %	45 %	43 %	42 %	41 %	34 %	34 %	32 %	34 %	34 %
Transit accessibility										
Low (Quartile 1)	16 %	14 %	13 %	11 %	11 %	12 %	14 %	14 %	11 %	14 %
Medium-low (Quartile 2)	20 %	19 %	19 %	21 %	22 %	25 %	26 %	24 %	23 %	23 %
Medium-high (Quartile 3)	22 %	26 %	28 %	29 %	27 %	30 %	28 %	30 %	32 %	30 %
High (Quartile 4)	42 %	42 %	41 %	40 %	40 %	33 %	32 %	32 %	34 %	34 %
Mode use - weekly trips										
Active transport	2.65 (2.74)	2.10 (2.53)	2.09 (2.43)	2.34 (2.56)	2.79 (2.90)	3.85 (2.82)	1.87 (2.41)	1.89 (2.26)	1.92 (2.24)	2.17 (2.58)
Driving	2.06 (2.69)	2.81 (2.92)	2.67 (2.76)	2.48 (2.66)	2.61 (2.80)	1.08 (2.07)	2.44 (2.20)	2.13 (2.02)	2.12 (2.04)	2.17 (2.07)
Public transport	3.03 (2.64)	1.01 (1.92)	1.25 (2.00)	1.37 (2.13)	1.48 (2.29)	1.73 (1.89)	0.53 (1.47)	0.26 (0.87)	0.37 (1.07)	0.52 (1.29)
Commuting patterns										
Commute time by driving										
(Under 15 min)	31.2 %	60.5 %	51.2 %	44.8 %	47.0 %	–	–	–	–	–
(15 to 30 min)	22.4 %	27.6 %	31.5 %	31.9 %	30.5 %	–	–	–	–	–
(30 to 60 min)	30.6 %	11.8 %	16.2 %	21.5 %	21.2 %	–	–	–	–	–
(60+ min)	15.7 %	0.1 %	1.1 %	1.8 %	1.3 %	–	–	–	–	–
Weekly telecommuting days	0.55 (1.26)	2.39 (2.25)	2.10 (1.99)	1.97 (1.90)	1.93 (1.84)	–	–	–	–	–

composed of 3443 observations from 1483 respondents. For the purposes of this work, people relocating within the same accessibility range are not treated as movers. Within workers, between 10 % and 20 % of the respondents relocated home at any given survey wave. For non-workers, this share is slightly lower than 10 %, most likely due to the higher age of this subsample compared to employed respondents. Fig. 2 shows the detailed distribution of all movers in terms of their accessibility levels before and after their home relocation. For both subsamples, most personal characteristics remain largely stable over time. The only characteristic for which there is a slight trend is yearly income, which slightly increases each wave for both workers and non-workers, consistent with inflation over the years. For each subsample, residential accessibility levels, both local and regional, remain largely stable over the five waves. This, together with the information shown in Fig. 2, indicates that home relocations don't take place majorly in one direction. Although there is a larger representation of people living in higher accessibility areas, all accessibility groups are represented by at least 10 % of the sample at any point in time for both subsamples.

Mode-use patterns, on the other hand, do display larger variations over time for both subsamples. These effects are consistent with pandemic-related trends: a reduction in the use of active modes and public transit, particularly large for the latter, and an increase in driving. For workers, COVID-related effects can be seen on commuting patterns, with an increase in the frequency of telecommuting and a reduction in the share of longer commuting times.

Fig. 2. Accessibility levels of movers before and after relocation.

5.2. *Frequency of mode-use modeling*

Results for the two sets of estimated models are presented in Table 2. Each of these models presents, for workers and non-workers respectively, the impact of different factors on the weekly frequency of use of each mode of transport. Through wave fixed effects, each model measures the change in weekly trips for each transport mode compared to 2019 while keeping other factors fixed. These fixed effects reveal clear pandemic-related shifts in travel behavior for both workers and non-workers. Transit suffered the steepest declines in 2021, with a reduction of −1.27 trips per week for workers, and − 1.16 trips per week for non-workers, keeping all else constant at their mean. Moreover, both groups showed only a partial recovery through 2024. Active modes dropped but rebounded fully for workers by 2024, while remaining depressed for non-workers by −1.39 trips per week, ceteris paribus. Driving frequency increased and stayed elevated, confirming a lasting pandemic-induced shift toward car reliance. These wave fixed effects not only describe but also control for the underlying pandemic-related trends shown in the descriptive analysis. Most importantly, these effects allow the isolation of the effects of the remaining independent variables.

The effects of income and age present expected results, with higher-income groups using transit less, while older adults tend to drive more. Small gender differences are found only for active modes, with women having −0.13 active trips per week in the workers group, and − 0.31 active trips per week in the non-workers group, when keeping all else constant. Among workers, each additional household member was associated with small but statistically significant increases in active transport use (+0.11 trips/week) and transit use (+0.15 trips/week), while having children under the age of 12 showed offsetting effects, slightly increasing driving (+0.15 trips/week). Notably, these patterns were either weaker or non-significant for non-workers, suggesting household structure plays a more limited role for this group. On the other hand, the effect of each car in the household has marked effects in expected directions: increasing driving (workers: +0.84 trips/week; non-workers: +0.75 trips/week), and decreasing use of active modes (workers: −0.55 trips/week; non-workers: −0.52 trips/week) and public transit (workers: −0.47 trips/week; non-workers: −0.36 trips/week), ceteris paribus.

The effects of exposure to different accessibility environments are the main results of interest from these models. First, the value of the time-decay exponent (α) reveal mode-specific adaptation rates to changes in the built environment. For workers, transit use adapts fastest to accessibility changes (α = 1.09), followed by driving (α = 0.83) and active modes (α = 0.73). Non-workers show a similar hierarchy but with transit levels adapting even faster (α = 1.13) and driving levels slower (α = 0.73).

Given that the proportional cumulative indicator PCET is a measure constructed based on an individual's history, the interpretation of the marginal effects is not direct, and is better understood through the scenario-based analysis provided in the next section. However, the direction and magnitude of these coefficients can be analyzed comparatively. Fig. 3 illustrates this for both subsamples, showing that the effects of exposure have expected directions for both subsamples. Exposure to higher local and regional accessibility areas has a direct impact on promoting higher use of active modes and decrease driving, whereas the opposite happens with exposure to lower local and regional accessibility areas. The differing effects of exposure to local accessibility environments on active mode are slightly larger in magnitude than those of regional accessibility on the frequency of driving. In the case of transit, for both subgroups the effect is not only comparatively smaller, but it displays an effect that is not strictly increasing. Whereas in other modes higher accessibility levels correspond to higher usage, the highest accessibility levels don't correspond to the highest positive impact on the use of public transport.

The random-effects structure reveals substantial between-person heterogeneity across all models, with intraclass correlation coefficients (ICCs) ranging from 0.36 to 0.49. This indicates that 36–49 % of the variance in mode use frequencies is due to individual differences rather than measured predictors. Workers and non-workers show comparable

Table 2
Weekly mode use – workers and non-workers model results.

	Workers			Non-Workers		
	Active	Driving	Transit	Active	Driving	Transit
Time-decay exponent	α = 0.73	α = 0.83	α = 1.09	α = 0.81	α = 0.73	α = 1.13
Intercept	2.56 ***	0.01	3.31 ***	2.73 ***	−1.66 ***	1.49 ***
w2 (2021)	−0.53 ***	1.24 ***	−1.27 ***	−1.96 ***	1.21 ***	−1.16 ***
w3 (2022)	−0.43 ***	0.99 ***	−1.13 ***	−1.86 ***	1.01 ***	−1.39 ***
w4 (2023)	−0.21 *	0.86 ***	−1.11 ***	−1.81 ***	1.11 ***	−1.28 ***
w5 (2024)	0.17	1.09 ***	−1.00 ***	−1.39 ***	1.19 ***	−1.05 ***
Personal characteristics						
Yearly income	0.01	0.01	−0.02 ***	−0.01	0.02 **	−0.02 ***
Age in 2019	−0.01 **	0.03 ***	−0.02 ***	0.00	0.03 ***	0.00
Gender [1 = woman]	−0.13 *	−0.06	0.08	−0.31 ***	0.01	0.06
Household size	0.11 ***	−0.04	0.15 ***	0.08	0.13 **	0.02
Children in the household	−0.04	0.15 ***	−0.17 ***	−0.03	0.05	−0.04
Cars in the household	−0.56 ***	0.84 ***	−0.47 ***	−0.54 ***	0.75 ***	−0.36 ***
Commuting characteristics						
Transit commute time (ref.: under 15 min)						
(15 to 30 min)	−0.29 ***	−0.22 ***	−0.24 ***	–	–	–
(30 to 60 min)	−0.43 ***	0.41 ***	0.49 ***	–	–	–
(60+ min)	−0.50 **	0.38 ***	0.62 ***	–	–	–
Weekly telecommuting days	−0.10 ***	0.20	0.42 **	–	–	–
Accessibility exposure measures						
WalkScore						
PCET to Low (0–50)	−1.14 ***	–	–	−0.99 ***	–	–
PCET to Mid-low (50–70)	−1.05 ***	–	–	−0.50 **	–	–
PCET to Mid-high (70–90)	0.04	–	–	0.64 ***	–	–
PCET to High (90–100)	3.02 ***	–	–	3.22 ***	–	–
Transit accessibility						
PCET to Low (Q1)	–	1.32 ***	−0.22	–	0.74 **	0.07
PCET to Mid-low (Q2)	–	1.02 ***	0.48 ***	–	0.87 ***	0.13
PCET to Mid-high (Q3)	–	−0.04	0.48 ***	–	0.14	0.39 ***
PCET to High (Q4)	–	−2.00 ***	0.28 **	–	−1.49 ***	0.24 **
σ2	3.17	2.78	2.18	2.37	1.69	0.95
τ00 person	1.99	2.21	1.92	2.16	1.61	0.54
ICC	0.39	0.44	0.47	0.48	0.49	0.36
N person	3067	3067	3067	1483	1483	1483
Observations	7219	7219	7219	3443	3443	3443
Marginal R2	0.25	0.32	0.19	0.27	0.25	0.15
Conditional R2	0.54	0.62	0.57	0.62	0.62	0.46

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

ICC magnitudes, though non-workers exhibit slightly lower person-level variance (τ00) in transit use. To evaluate goodness of fit of the multilevel models, the marginal R^2 value represents the variance explained solely by fixed effects (i.e. time-varying predictors like relocation or car ownership). The conditional R^2, on the other hand, reflects the model's total explanatory power including both fixed effects and random effects (i.e. individual heterogeneity). The conditional R^2 values (0.46–0.62) suggest the combined fixed and random effects explain nearly half to two-thirds of variance. On the other hand, the marginal R^2 values (0.15–0.32) confirm a substantive role of time-varying predictors. These results justify the multilevel approach while highlighting unexplained individual-specific factors shaping travel patterns, which is expected for an individual-level travel behavior model.

5.3. Scenario-based analysis

This scenario analysis has the goal of illustrating how the estimated models may represent the temporal evolution mode-use trajectories. By fixing all variables except for PCET, as described in Section 4, this analysis shows how home relocation may reshape mode-use behavior over time. In the first scenario-based analysis, four profiles of people are proposed, all of which are assumed to maintain all characteristics constant except for a home relocation that corresponds with a change in accessibility levels (Fig. 4). Profiles P1 and P2 relocate from a lower to a higher accessibility level, while profiles P3 and P4 do the opposite. The weekly trips for each profile at years −2 and − 1 (pre-move years) represent what the models predict for any person who has been living long term in each profile's initial built environment. For example, P4 initially in a high local and regional accessibility, as a worker is predicted to perform 5.3 trips/week by active modes, 0.6 trips/week by driving, and 2.5 trips/week by public transport. It is important to note that, although these absolute values may appear modest at the individual level, they reflect population-level averages that include both frequent and non-users of each mode. A more actionable interpretation is that for every 1000 workers in high-accessibility environments, we'd expect ~5300 weekly active trips and ~ 2500 transit trips, compared to just ~600 driving trips, a ratio strongly favoring sustainable modes.

The residential relocation for all profiles occurs at year zero, and the gradual evolution of the frequency of travel by each transport mode is seen in following years. This gradual evolution is the main goal of this illustrative analysis and showcases the potential of this modeling approach. The impacts of built-environment exposure are consistently largest for active transport and smallest for public transport. Workers and non-workers present small response patterns in their mode use. Non-workers exhibit lower baseline travel frequencies, particularly for driving and public transport. Additionally, they present slightly smaller responses to regional accessibility changes, especially for driving. The impacts of built-environment exposure are largest for active transport and smallest for public transport.

Building on the first relocation scenarios, the influence of combined changes in built environment and car ownership are analyzed. Four additional profiles (P5–P8) mirror the accessibility transitions of P1–P4 but incorporate realistic vehicle adjustments: selling a car when moving to higher-accessibility areas (P5, P6) or acquiring one when moving to lower-accessibility zones (P7, P8). All other characteristics remain fixed as in the initial analysis, ensuring isolation of these joint effects. The

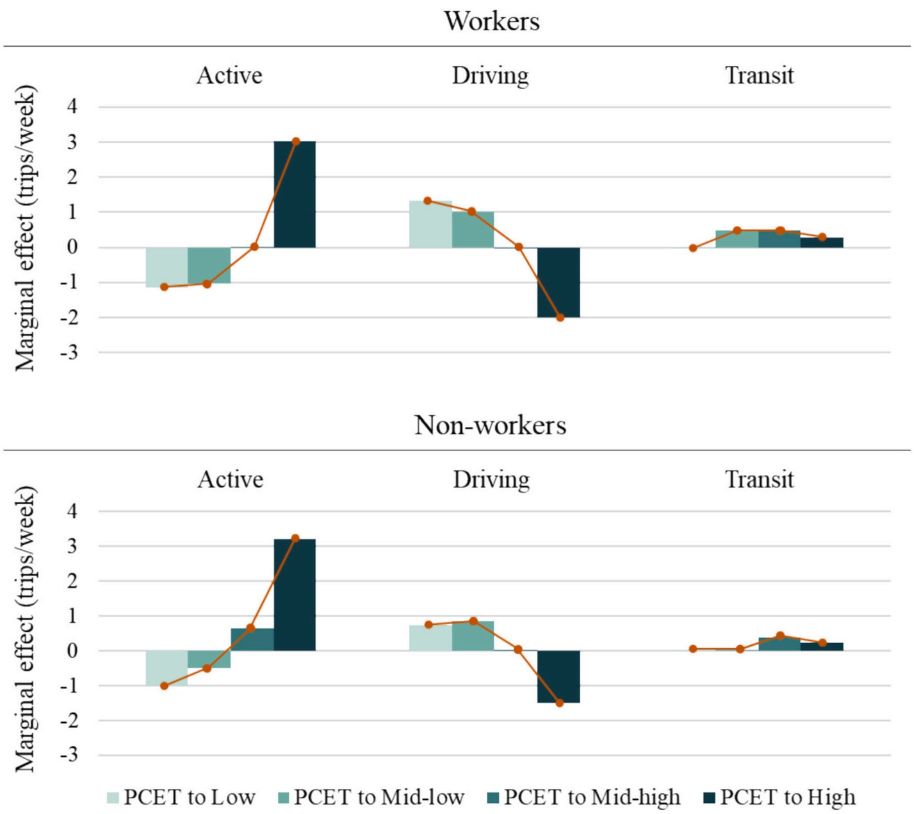

Fig. 3. Effects of proportional cumulative exposure (PCET) to accessibility levels on mode use frequency. Non-significant coefficients are displayed as zero.

results from this analysis are shown in Fig. 5, illustrating the joint effects of relocation and car ownership changes and how they differ between modes.

It is clear how the effect of car ownership decisions add to the effects of the built environment during a home relocation. These effects differ by mode both in absolute contribution as well as in the share that this contribution represents compared to the effects of exposure to local and regional accessibility levels. Expectedly, the largest impacts of car ownership are on the frequency of driving. This is followed by the frequency of active trips, which is reduced by car ownership. However, although car ownership has the smallest absolute impact on the frequency of transit use, it represents a considerable contribution compared to the impact of changes in local and regional accessibility levels. Again, differences between workers and non-workers exist, but the overall trends are the same. The findings from these scenarios make it clear that when people relocate, both the new neighborhood and whether they change their car ownership work together to shape their mobility patterns.

6. Discussion

The longitudinal modeling approach presented in this work reveals how residential mobility – shaped by built-environment exposure, mobility decisions such as buying a car, and pandemic-related disruptions –reconfigures urban travel behavior. The results not only provide valuable knowledge into changes in mode-use patterns over time and the factors that mediate them. They also provide actionable insights toward land-use and transport policy.

The exposure measures and longitudinal models in this work are able to reflect a critical insight: behavior adapts gradually to built-environment changes. While prior relocation studies emphasized immediate and relatively stable adjustments to new built environments (Chang et al., 2010; Chatterjee and Ma, 2007, 2009), the current findings suggest that adaptations unfold more gradually. This distinction is important because it highlights that behavioral responses are not instantaneous, but rather evolve as individuals adjust in their use between active travel, driving, and transit. Moreover, by adopting a multimodal lens, this study reveals substitution dynamics across modes that earlier relocation research overlook by focusing on a single mode (Faber et al., 2025; Xu et al., 2024). The scenario-based analysis effectively isolates these temporal effects, showing that mode-shift responses unfold over years, not immediately post-relocation. This graduality highlights a key challenge for short-term policy evaluations. Interventions like zoning reforms or transit investments, which already require spans of years to implement, may require even longer timelines to manifest their full impacts after implementation. These challenges could be addressed by pairing infrastructure and service changes with measures of soft policies aimed at behavioral changes during transition periods. These could include temporary car-use disincentives and public transport incentives. These gradual results in this work recognize that a focus on the turning point after which behavior becomes more consistent is essential to assess long-term efficacy.

Results confirm that distinct built environments, reflected through distinct local and regional accessibility levels, exert different effects across transport modes. These findings underscore the importance of disentangling local and regional accessibility effects, a distinction emphasized by the literature (Handy, 1993, 2020; Manaugh and El-Geneidy, 2012), as their divergent impacts on travel behavior require targeted policy interventions. Active transport shows the strongest response, reinforcing the centrality of local accessibility in sustainable urban mobility. Driving also presents a direct response, where areas with higher regional accessibility by public transit result in decreasing frequency of car use over time. Public transport, on the other hand, reveals more complex dynamics. Its responsiveness to regional accessibility is weaker, and results align with previous evidence of non-linear effects (Negm and El-Geneidy, 2024; Schimohr et al., 2025; Victoriano-Habit and El-Geneidy, 2024). That is, frequency of public transport use is not highest where regional accessibility is highest, and transit gains are most

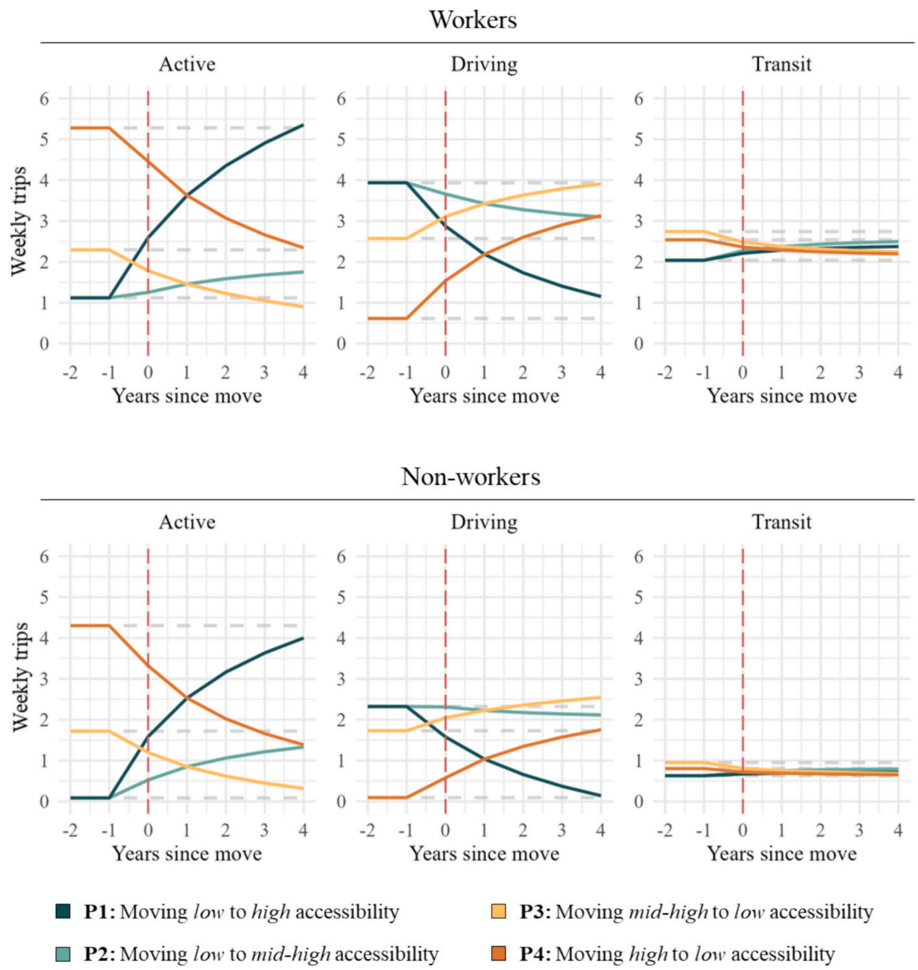

Fig. 4. Home relocation impacts on mode-use frequency.

viable in moderate-accessibility areas. In very high-accessibility settings, active travel becomes more attractive and feasible, reducing the relative need for transit, a pattern consistent with the findings of earlier studies. Further, results explicitly suggest that there is replacement in mode use, where people relocating in the highest accessibility areas replace both driving and transit trips by active transport.

The exposure measure used in this work revealed distinct adaptation patterns across transport modes. For both workers and non-workers, public transport use adjusts most quickly to built environment changes due to home relocation. This rapid transit adaptation for both subgroups suggests this mode has less behavioral inertia post-relocation compared to other modes. This makes residential moves a short-term potential window for transit agencies to capture new users. Interestingly, workers adapt faster to changes in the built environment when it comes to driving patterns, while non-workers adapt faster to active mode changes. Notably, the estimated time-decay exponents for all modes and subgroups present values close to $\alpha = 1.0$ (from 0.73 to 1.13). Although the mode-specific exponents yield better model fits than the original PCET formulation by Wasfi et al. (2016), the increases in marginal R^2 values compared to the original measure were modest ($\Delta \leq 0.01$). This suggests that, despite the original PCET measure not capturing certain mode-specific differences, it may still provide reasonable approximations of travel behavior trajectories.

Results support the relevance of improving local accessibility, that is higher diversity and proximity of activities, around residential areas. These neighborhood-scale measures, although seemingly the most effective in promoting sustainable mode shifts, require a larger effort and time span to implement than purely transport measures. This highlights the importance of shorter-term measures such as enhancing regional mobility in low accessibility areas through public transport. Given the non-linear relationship between regional accessibility and transit use, it particularly highlights the need to improve transit services in moderate-accessibility areas. This supports recommendations by previous studies, as supporting these areas through transit-system improvements can have highest impact on ridership by promoting access where active modes cannot (Negm and El-Geneidy, 2024; Victoriano-Habit and El-Geneidy, 2024).

Residential relocation and car ownership changes often coincide, compounding their impacts on travel behavior. Our results indicate that acquiring a car significantly shifts mode use from both active transport and transit toward driving. This underscores the need for policy interventions that pair local and regional accessibility improvements with car-reduction incentives. However, strategies like this should be anchored by affordability and equity. Lower-income populations, shown by the results to be more reliant on transit and less likely to own cars, are particularly prone to displacement from walkable neighborhoods (Bereitschaft, 2023). Results from this study suggest that such displacement not only exacerbates housing inequities but actively undermines sustainable transport goals.

Conversely, household structure and presence of children showed limited influence, particularly for non-workers. These results diverge from previous studies suggesting these factors to be some of the most relevant triggers of behavioral change (Lee et al., 2017). However modest, there was a consistent reduction in transit use among workers with children, as well as a small increase in the frequency of driving. This suggests that current transit systems may inadequately serve

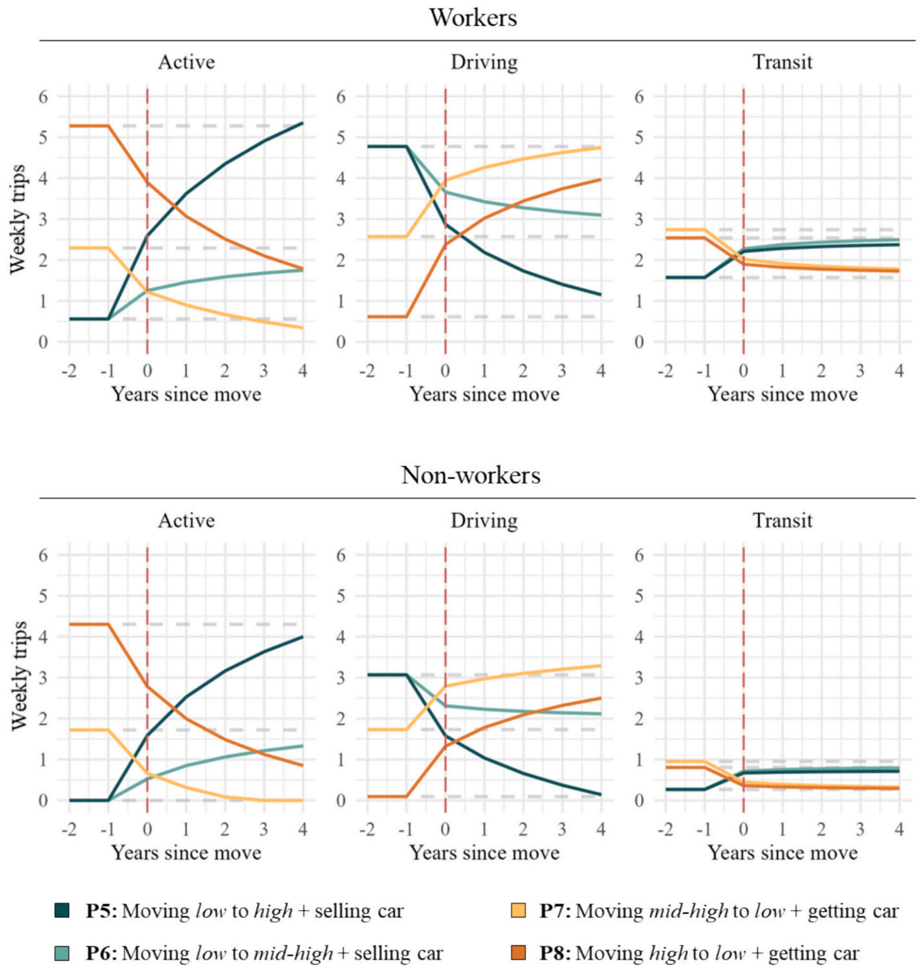

Fig. 5. Home relocation and changes in car ownership impacts on mode-use frequency.

mobility needs related to childcare, consistent with previous studies (Soukhov et al., 2025). Though the magnitude of these effects is smaller than built environment or car ownership factors, these results may still highlight an equity gap. Families with young children may face constrained mobility options, even in high-accessibility areas.

Workers and non-workers exhibited significative differences in travel frequencies, mode usage, and responses to built environments. This is consistent with previous studies (Chowdhury and Scott, 2020; Dharmowijoyo et al., 2018; Victoriano-Habit and El-Geneidy, 2024) and confirms the need to analyze both samples separately. However, the direction and relative responsiveness to changes in accessibility levels remain aligned across groups. This suggests that policies targeting accessibility improvements, car-reduction incentives, or transit upgrades would yield benefits for both groups, even if absolute impacts differ.

The longitudinal data in this work showed mode-dependent trends in frequency of travel that are consistent with previous studies (Abduljabbar et al., 2022; Long et al., 2023; Wang et al., 2022). Namely, a movement toward more car mobility with a declining use of active and public transport modes, particularly steep on the latter. Results showed a relative stabilization of post-covid trends in mode use. It is relevant to note that the inclusion of these pre-, during-, and post-pandemic trends in this study is itself noteworthy. They underscore how the pandemic reshaped the context in which mode-choice decisions are now made. This evolving context is central to this study's relevance.

Crucially, these changing trends highlight why longitudinal data and modeling are required: they simultaneously control for pandemic-era disruptions while unraveling the underlying effects of built-environment exposure and life-stage decisions. In this context, the contribution of a random effects structure is consistent with prior longitudinal work (Victoriano-Habit and El-Geneidy, 2023; Wasfi et al., 2016). Together, these findings demonstrate both the potential of this modeling approach for capturing behavioral adaptation and the nuanced ways different population segments adjust their travel patterns following residential moves.

7. Conclusion

This study advances our understanding of how urban travel behavior evolves in response to built-environment changes and other lifestyle changes in the post-pandemic era. Through longitudinal analysis of Montréal residents, results demonstrate that residential relocation, car ownership decisions, and local and regional accessibility exposure collectively reshape mode choices. Distinct patterns arise across the three major transport modes: active transport, driving, and public transit. The multilevel modeling approach reveals three key insights: (1) accessibility changes exert gradual but mode-specific effects, with active transport showing the strongest response; (2) while workers and non-workers show varying baseline travel patterns, both groups exhibit comparable directional responses and similar relative effect magnitudes in their mode use frequency as a response to local and regional accessibility improvements and changes in car ownership; and (3) car ownership decisions significantly mediate these effects, potentially generating compounding effects with relocating to different built environments. These findings advance the methodological integration of longitudinal exposure measures in mobility research.

Potential limitations from this study warrant future research. The scenarios presented here, while illustrative, point to the need for deeper analyses that explicitly capture individual paths of change in lifestyle and how they result in changing travel behavior. Future studies could address this in multiple ways. This work assumes symmetric effects when moving between different accessibility levels, yet future studies may assess potential directional differences (e.g., low-to-high versus high-to-low accessibility transitions). The worker/non-worker dichotomy presented in this study, although meaningful, could be refined in future works. This could be achieved through latent class analysis to identify subgroups with distinct adaptation patterns. The use of discrete accessibility ranges, though policy-relevant, may simplify more continuous environmental relationships on which future research could focus. Additional granularity could be gained by disaggregating active modes (walking versus cycling), examining further trip purposes, or considering temporal variations in accessibility levels throughout the day. While this work tested but found no significant pandemic interaction effects, comparative analyses with pre-pandemic data could reveal evolving behavioral norms. This study's modeling approach, while robust to individual heterogeneity through random effects, cannot fully resolve the inherent endogeneity in built environment-travel behavior relationships. Methodological extensions such as structural equation modeling, random coefficient specifications, or quasi-experimental designs could provide stronger causal identification in future work, as well as more explicitly address potential residential self-selection concerns. Nevertheless, this work establishes a replicable framework for studying mobility transitions amid evolving urban contexts.

CRediT authorship contribution statement

Rodrigo Victoriano-Habit: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ahmed El-Geneidy:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

Acknowledgements

The authors would like to thank James DeWeese for his help in designing the survey. Particular thanks go to Rania Wasfi for helping in reviewing and providing feedback on the analytical approach. The authors would also like to thank Hisham Negm for his help in building the maps in this work. This research was funded by The Canadian Institutes of Health Research (CIHR) and The Natural Sciences and Engineering Research Council of Canada (NSERC) Collaborative Health Research Projects (CHRP) Program (CIHR CPG-170602, CIHR LIM-192221 and CIHR PJT-195797, NSERC CHRPJ 549576-20).

Data availability

The data that has been used is confidential.

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